The Role of People vs. Places in Individual Carbon Emissions
Online Appendix

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A Data Appendix

A.1 Additional Details on Variable Construction

- **Missing and imputed variables:** I follow Chetty and Hendren (2018) and Bailey et al. (2024) in treating all imputed variables as missing, unless otherwise described. Dollar values are inflated to 2019 values using the Consumer Price Index (CPI). Throughout the analysis I use demographic and household characteristics to control for selection on time-varying observables, I use work characteristics to construct commuting variables, and I use home characteristics in the second half of the paper to characterize places and study associations between built environment and place effects.

- **Flags**: Residential energy expenditure is flagged as "allocated" (to zero) for many households in the 2014 ACS if they checked a box indicating that they did not use natural gas or fuel use and then left the expenditure question blank. Because of this, I make an exception to my rule of dropping flagged variables and allow for residential energy to be allocated to zero based on the checkbox question.

- **Work characteristics:** For each individual I retain information on employment status, place of work, weeks worked last year, and hours worked last week. I allow place of work tracts or more detailed geographies to be missing, but I drop observations if county of work is missing (unless the individual is unemployed or works from home, in which case I impute their place of work as their home). I also allow current employment status to be missing if weeks worked last year and hours worked last week are not missing and not imputed. In 2008-2018, the weeks worked variable is binned; I follow Chetty and Hendren (2018) and assign the midpoint to all individuals in the bin. Since these variables are an input into my measure of commuting energy use, I use the midpoint from the bin for all years to keep the variable definition consistent.

- **Demographic characteristics** I control for age using bins: 18-24, 25-29, 30-34, 35-39, 40-49, 50-64, and 65+. I control flexibly for number of children in the household using categorical variables for 0, 1, 2, or 3+ kids. As highlighted in Card, Cardoso, and Kline (2016), the normalization choice for categorical variables does not affect the estimated size of the place variance component or the variance component of the sum of fixed and observable household effects, but it does affect the relative sizes of the place and unobserved household effects, as well as the estimated covariances. Throughout my analysis, I choose the age bin 40-49, no college degree, male, white, and non-Hispanic as the omitted categories. Other than "white", these are the categories with the highest within-group variance in outcomes. Thus this normalization should err towards finding a larger unobservable person component relative to place component.

- **Observations dropped due to missing utility data:** I exclude households from the sample if their residential energy costs are included in rent, or if their gas costs are included in their electricity bill, because I do not observe expenditures in those cases. As shown in Table G.1, households in this sample have significantly lower income, are less likely to own their home, live in a detached single family home, or commute by car, and are more likely to live in an urban neighborhood. For the subsample who would have been in the panel if not for this restriction, I estimate these households are more likely to have an increase in income, an increase in the number of children in the household, and go from renting to owning than the baseline sample. They are also twice as likely to move from an urban neighborhood to another urban neighborhood when moving. To the extent that you might worry that 1) households who live in the most urban neighborhood are most selected and would respond differently to changes in place than a more average household or 2) large changes in observable characteristics signal that estimates may be biased by accompanying large changes in unobservable characteristics, dropping these households from the analysis is likely to decrease any upward bias in place share estimates that could arise from violations of either the constant effects assumption or the exogenous mobility assumption.

- **Vehicle fuel economy:** I assume individuals that commute by car or taxi do so in a vehicle with annual national average fuel economy, using data from the Federal Highway Administration (2022). For motorcycles, I scale miles per gallon (mpg) by two (U.S. Department of Transportation 2015). This is a minor point as motorcycles account for only roughly 0.6 percent of vehicle miles driven (U.S. Environmental Protection Agency and Energy 2020). I also account for the fact that in general fuel economy is roughly 30 percent higher when driving on highways than in cities by adjusting mpg up by 19 percent relative to the national average for drivers whose average commuting speed exceeds 55 miles per hour (mph), and down by nine percent relative to the national average for drivers whose average commuting speed is below 40 mph (U.S. Environmental Protection Agency 2021). As a robustness check, I also use data from the National Household Travel Survey (Federal Highway Administration 2022) to estimate heterogeneous fuel economy values. I discuss the construction of these estimates in Appendix A.2.

- **Carpooling**: I divide carbon emissions by the number of carpoolers for individuals who report carpooling.

- **Emissions from public transportation:** I assign emissions factors to commutes by public transportation using estimates derived from the National Transit Database (NTD, Federal Transit Administration 2002-2019). Specifically, for each transit agency and year, I use reported data on fuel consumption and passenger miles traveled (PMT) by mode in order to estimate carbon emissions per PMT for six possible modes of commuting: subway or elevated rail, commuter rail, streetcar, bus, ferry, or taxi.[1] As with residential emissions, I assign fuel emissions factors using data from the U.S. Environmental Protection Agency 2018 and I assign electricity emissions factors using average values at the North American Electric Reliability Corporation (NERC) region level. After estimating mode-specific emissions for all reporting transit agencies, I estimate passenger mile weighted mode

1. NTD modes of commute are more granular than ACS modes of commute. I group heavy rail, monorail/automated guideway, light rail, and aerial tramway into the subway & elevated rail group. I treat commuter rail and hybrid railroad as railroad. I group streetcar, cable car, inclined plane, and trolleybus into the streetcar mode. Bus, bus rapid transit, and commuter bus all get categorized as bus. And lastly, I categorize demand response, demand response taxis, and vanpools as taxi.

emissions factors in each urban area, and assign individuals an emissions factor based on the urban area they live in. For individuals who live outside of an urban area with a reporting agency, I use their mode's national annual average emissions per passenger miles travelled to estimate emissions.

- **Emissions from walking or biking**: I assign zero emissions to commutes by walking or biking. This underestimates emissions from biking as electric bikes (i.e. e-bikes) grow in popularity. Unfortunately, I cannot distinguish in the ACS the kind of bikes commuters use, and in the majority of my sample traditional bicycles dominated the market. An important question for future research is how e-bike subsidies and local bike-share programs change commute mode choice and emissions.[2]

- **Commuting distance**: I estimate commute mileage using the GPS distance between reported home and place of work census blocks. To account for the fact that geodesic distances don't capture the indirect nature of roads, I re-scale my mileage estimates to match the national average commuting distance, by mode, reported in the NHTS. For individuals who only report their county of work but not their census block of work, I impute miles traveled using reported commute time and average commute speeds for people with similar residence-job geographic pairs. I use a similar imputation for individuals for whom the travel speeds implied by dividing estimated miles by commute time are infeasible – over 150 mph in a train,[3] or over 80 mph on average in other modes.

- **Number of annual commutes**: I estimate commuting days per week using reported hours worked last week and assuming people work eight hours a day up to five days a week, assuming people worked five days if they worked 40-50 hours a week, 6 days if they worked 50-60 hours in a week, and 7 days if they worked more than that. I assume everyone commutes twice a day, and that commuting behavior is consistent across all the weeks worked last year.

- **Identifying children:** I designate a household member a child and drop them from the analysis sample if they are under the age of 18, or if they are identified as a child via the Census' relationship to householder code.

A.2 Measurement Error in Household Carbon Emissions

There are several sources of measurement error in household carbon emissions from residential and transportation energy use. While an advantage of the ACS is that it makes observable many household characteristics that are unobservable in standard administrative datasets on energy use, making it possible to control for changes to household characteristics that are correlated with both changes to energy demand and move propensity and destinations and decrease potential bias from unobserved preference shocks, a disadvantage is that the survey nature of the data means that the outcome variables are constructed from a combination of survey responses (whose quality depends on household reporting) and local external data. This could introduce

2. Xu (2020) finds that bike commuting is more common in cities with bike share programs.
3. This is the fastest speed a train ever goes in the US, along a small segment of the Northeast Corridor.

bias in either estimates of household and place effects, estimates of the variance components, or both. Note that if errors are random but serially correlated within a household, both a naive variance decomposition and a KSS variance decomposition on a sample consisting of both stayers and movers will overstate the share of heterogeneity attributable to households; however, when I restrict to the mover only sample, the KSS correction accounts for serial correlation in the error term and gives unbiased estimates of variance components. Below, I discuss the various possible sources of measurement error, as well as potential biases that arise in my estimates as a result. In cases of greater concern, I discuss the construction of alternate variables used for robustness checks in the paper.

Household reporting of residential energy expenditures

Households may not accurately report energy expenditures. Inaccurate reporting could arise, for example, due to inattention to bills, or due to bias driven by the seasonality of energy expenditures – that is, if households use their last monthly bill to proxy for annual expenditures.

If household inattention is fixed it will be absorbed by the household effect. If inattention leads high types to overstate their expenditures, and low types to understate their expenditures, this would lead to an upward bias in the household component of heterogeneity, and vice versa. It is also reasonable to think that inattention may be random but serially correlated within household.

With fixed or random inattention, estimates of place effects themselves are unbiased. However, if moves are correlated with changes in attention, this could lead to bias in estimates of place effects. For example, if households move after positive income shocks, and higher income households pay less attention to their energy bills, *and* this inattention leads to systematic under- or over-estimation of expenditures, estimates of place effects with more inattentive residents would be biased.

Seasonality is unlikely to bias my estimates because surveys are sent out randomly, and therefore the season households were surveyed shouldn't be correlated with other components of the model.

Electricity prices

In the baseline specifications, I estimate electricity prices from total utility revenues divided by total utility customers, by county (using data from EIA Form 861). This introduces three sources of measurement error in electricity prices.

First, in counties served by more than one utility, I cannot match customers to the actual utility they are served by. If customers in an area can select their residential energy provider, this could lead to bias in the household component of heterogeneity. For example, if higher type customers are selecting into lower average price utilities, I will underestimate the household component of heterogeneity. Similarly, if there are several utilities serving different neighborhoods within the same county, this could lead to bias in the place component of heterogeneity. In particular, I will over-estimate consumption in neighborhoods served by more expensive utilities, and under-estimate consumption in neighborhoods served by cheaper utilities. If more expensive utilities generally serve lower consumption neighborhoods, this will lead me to underestimate the place component of heterogeneity.

Second, residential customers generally face a two-part tariff consisting of a fixed charge and a marginal volumetric charge, in which the marginal price can either be increasing or decreasing in consumption depending on the utility. Because I use average prices, calculated from utility residential revenues and quantities sold, I overestimate the average volumetric price and in turn underestimate consumption for everyone (more so for households in high fixed charge service territories). Moreover, for some utilities, marginal prices are either increasing or decreasing in consumption. When prices are increasing in consumption, I under-estimate prices faced by high-demand customers and over-estimate prices faced by low-use customers. This means I over-estimate quantities consumed by high-demand customers and under-estimate quantities consumed by low-demand customers, leading to an upward bias in my estimates of the household variance component. Conversely, if prices are decreasing in consumption, I underestimate the household variance component.

Borenstein and Bushnell (2022) estimate that in the US, roughly 37 percent of customers face increasing block pricing, and roughly 21 percent face decreasing block pricing, though in all cases the rate structure is fairly narrow. They also estimate that across territories, utilities that utilize increasing-block pricing generally serve lower demand customers on average. Thus, my estimates likely somewhat over-estimate variation across households within utility territories, and underestimate variation across territories. Overall, unobserved rate structures should lead me to estimate a lower bound on place-based heterogeneity and estimate an upper bound on preference-based heterogeneity.

Finally, residential rates can vary within utilities, and I don't observe which rate a household has selected. This leads to the same biases as not being able to observe which utility a customer chooses, discussed above. Additionally, I do not observe if a household has solar, and in many states solar customers face different price schedules with significant subsidies for selling generated power back to the grid. This lowers their average price per kilowatt hour (kwh), causing me to underestimate quantity consumed and in turn CO_2 from electricity purchased from the grid by these customers.

Alternate electricity price estimates for robustness checks

To test the sensitivity of my results to the issues described above, I construct several alternate estimates of residential electricity prices.

First, I account for fixed charges, closely following Borenstein and Bushnell (2022) in my approach. I supplement the EIA 861 data with annual data from the Utility Rate Database (URDB, OpenEI 2023), which contains utility-level data on rate schedules. I collect fixed charges from the set of utilities in the URDB that report detailed retail pricing information, using the median fixed charge in the standard tariff for each utility-state pair in cases in which utilities reported multiple rates.

The URDB is not perfectly populated, and is much sparser in the earlier years[4]. In cases where I observe a fixed charge for some but not all years of a utility-state pair, I impute values for missing years using values from the closest available year. If I observe two different fixed charges with missing years in between, I impute the value for those missing years using the mean of the observed values.

I then estimate the variable price component for each utility-state pair by combining my fixed charge estimates with annual total revenue, generation, and customer data from the EIA 861. I subtract estimated total fixed revenue (fixed charge times number of customers) from total revenue reported in EIA 861, and then divide variable revenue by total sales to get a variable price per kwh of electricity. Consistent with the fact that fixed charges are generally a low share of the two-part tariff (I estimate that across my sample fixed charges make up roughly 9 percent of total revenues), the distributions of average and variable prices appear similar. I proceed as in the baseline estimation, constructing a county-level average variable price as the customer-weighted mean variable price of all utilities serving a given county. In the microdata, for counties without a variable price estimate, I continue to use my average price estimate.

Second, I account for the fact that sometimes utility tariffs follow a tiered pricing schedule, in which marginal prices either increase or decrease with the quantity of electricity consumed. URDB also contains some information on price schedules with tiered pricing, but these data are even more complex and sparse than the fixed charge data. I have no way of knowing which customers choose a rate with tiered pricing, or even what share of customers are on each schedule. To bound the issues that could arise from tiered pricing, I gather information on the mean price difference between the top and bottom price for each utility-state-year. I do this separately for tariffs with increasing block rates vs. decreasing block rates. As with the baseline and variable price estimation, I estimate a county-level average price difference for increasing and decreasing block prices. I then estimate top and bottom county-level prices as the variable price in that county plus/minus half the price difference. I estimate the price step as being at the median county level quantity consumed, as estimated using average variable price.

I then explore three bounding scenarios. In the first, I assume that every customer who lives in a county where an increasing block price schedule is available chooses the increasing block price schedule. In counties without any increasing block price schedules, customers are assigned the average variable price. In the second, I make an analogous assumption but with decreasing block prices. Finally, I consider a selected scenario, in which customers with below median electricity costs for their county select into an increasing block pricing schedule, while customers with above median electricity costs for their county select into a decreasing block pricing schedule. Note, this selected scenario also yields some insight into the bias that would arise from customers selecting across utilities based on price. While none of these perfectly capture the actual price schedules faced by all customers in the data, they should provide some bounds on the bias incurred by not accurately observing marginal prices.

Using estimated variable prices or assigning tiered pricing schedules to households does not meaningfully impact variance component estimates (Table G.9).

4. Coverage of EIA 861 utilities goes from 16% in 2000 to 79% in 2019.

Electricity carbon emissions factors

I estimate the carbon emissions intensity of electricity using average emissions factors at the NERC region. This does not capture the fact that electricity is generated from different fuels throughout the course of the day (e.g., solar peaks in the afternoon) and across seasons (e.g., there is less solar in the winter). The error in household carbon emissions that results from this is likely serially correlated within household, and can be accounted for in the mover-only KSS specification. However, if consumption profiles are also correlated with these patterns, my estimates of household carbon emissions will be biased. For example, if low-type users consume more electricity when marginal emissions are higher, then I would tend to under-estimate their carbon emissions and over-estimate the household component of heterogeneity.

Alternate electricity emissions estimates for robustness checks

In the baseline specifications, I estimate household electricity emissions using average emissions factors computed from aggregate production and fuel use at the NERC region level. Conceptually, I believe that this is the right emissions factor to use because a change in the place effect simultaneously affects all residents of the place, leading to non-marginal changes in electricity consumption. However, I also construct a measure of household electricity emissions using marginal emissions factors. Note that this doesn't address the issue of emissions varying across hours and seasons and that variation possibly being correlated with usage patterns, because I cannot distinguish differences in marginal emissions across households within a place.

I follow Borenstein and Bushnell (2022) and estimate marginal emissions for each of nine regions – the eight reliability regions of the NERC, with the Western Interconnection (WECC) region split into California and non-California sub-parts – by regressing hourly carbon emissions on hourly load using the following specification

$$CO_{2it} = \beta Load_{it} + \alpha_{mh} + \gamma_i LoadInterconnect_{-it} + \epsilon_t$$

where α_{mh} represents month of sample by hour of day fixed effects and γ_i represents the marginal effect of load from other parts of the interconnect onto carbon emissions in a given region. Marginal emissions from electricity load in a region are then given by $\beta_i + \sum_{j \neq i} \gamma_j$. In practice, allowing for the impact of other regions' load on marginal emissions does not make a big difference.

I construct hourly carbon emissions from power plants in each region using data from the Continuous Emissions Monitoring System (U.S. Environmental Protection Agency 2006-2019). I extend estimates of hourly load from Cicala (2022b) (Cicala 2022a) through 2019 using data from the Federal Energy Regulatory Commission's Form-714 Survey (Federal Energy Regulatory Commission 2021). In a few region-year pairs where supplementary data were required but unavailable, I interpolate region marginal emissions from the nearest available year.

Using marginal emissions estimates to construct carbon emissions from electricity increases the share of covariance attributable to places by about seven percentage points relative to baseline estimates (Table G.9).

Natural gas and other residential heating fuel prices and emissions

Many of the same price measurement errors arise with natural gas as with electricity, but generally individuals have less choice over their utility, fixed charges are larger, and there is less prevalence of block pricing. Unlike electricity, fuel emissions factors for other fuels are the same regardless of where a household lives. However, in the case of natural gas a significant source of emissions is upstream methane leaks, which I don't consider in this analysis.

Assignment of heating fuel

I estimate carbon emissions from fuel use by assigning all expenditures on "other home heating fuels" to the fuel reported as the primary fuel. If a household has non-zero other fuel expenditures, but it doesn't list a primary fuel, I impute its primary fuel based on the most commonly used primary fuel among other survey respondents in their state and year (out of residual oil, propane, and wood). If in reality households use more than one heating fuel, or use a heating fuel other than the one I imputed for them, there will be error in my measurement of carbon emissions, both as a result of dividing expenditures by the wrong fuel price, and as a result of assigning the wrong carbon emissions factor. I will overestimate household carbon emissions if reported or imputed fuel prices are lower than actual average fuel prices faced by the household, or if reported or imputed fuel types have higher emissions factors than the fuels actually used.

If I tend to overestimate carbon emissions from heating fuels for otherwise high-type households and underestimate carbon emissions from heating fuels for otherwise low-type households, then my household variance component will be biased upward, and vice versa. Moreover, if moves are correlated with shocks to unobserved fuel components, this could lead to bias in my estimates of place effects. For example, if a household uses the same heating fuel everywhere they live but doesn't report this fuel, if they move to a place where their neighbors use an on average higher emissions heating fuel, I would overestimate the place effect. In practice, the share of households reporting non-zero energy expenditures on heating other than electricity or natural gas is small, and my estimates are not meaningfully affected when I exclude other heating from the calculation.

Commuting distances:

Because I estimate commute miles from geodesic distances between coordinates, I will underestimate speed and miles traveled for individuals who have less direct commutes. If place-based constraints (e.g., the result of living in a gated community or a neighborhood with many winding roads and cul-de-sacs) shape the directness of a commute, and if these types of neighborhoods tend to be farther from employment centers and have longer commutes to begin with, then I will underestimate the place component of spatial heterogeneity.

Additionally, I impute miles for the people for whom I don't observe census block of work using average mph for home and place of work county pairs. This will lead me to overstate commute distances for people with slower than average commutes, and understate commute distance for people with faster than average commutes. If faster than average commutes are also longer than average, then I will underestimate the household component of spatial heterogeneity. The "Commute from hrs" rows in Table G.9 show that my estimates are not sensitive to using a simpler measure of commute distance, calculated from simply dividing reported commute time by the average national commute speed, 32 mph (Federal Highway Administration 2022), suggesting that errors in commute speeds are unlikely to bias my estimates.

Total commuting miles:

I use weeks worked last year to estimate total commuting from typical commuting behavior last week. This assumes that hours worked are stable, that people work at the same place all year, and that information about commutes reported for last week is representative of commutes generally. Any deviations along these dimensions introduces measurement error into my outcome. While such errors are more likely to arise for lower income households with less job stability, it is unlikely that it results in a systematic over- or under-estimate of commute miles on average.

Indeed, the results in the "Commute from hrs, fixed num." row in Table G.9 are qualitatively similar to the baseline estimates.

Commuting emissions:

I assume everyone drives a vehicle with the annual national average fuel economy, using data from the NHTS (Federal Highway Administration 2022). This is a significant oversimplification – and my inability to observe fuel economy is a significant limitation of my data – as it ignores patterns of heterogeneity in fuel economy both across commute lengths and across regions. If people with longer commutes drive more fuel efficient vehicles, I will overstate heterogeneity. On the other hand, if people who want to conserve on gas both buy more fuel efficient vehicles and choose to have shorter commutes, I will understate heterogeneity. The bias in my estimates of relative shares is more ambiguous. As with my broader analysis, there is a question of whether regional patterns in fuel economy are driven by individual preferences or place-based differences. If regional variation in fuel economy is driven by individual preferences, I will understate the relative importance of the person component in spatial variation. On the other hand, if they are driven by local norms or place characteristics such as, for instance, the availability of parking and width of roads, I will understate the relative importance of the place effect.

Additionally, if households change their mode of transit over the year, or if they use multiple modes of transit in a single commute, I do not capture this variation. For example, if households report taking public transit as their primary mode, but in reality they drive part of the distance of their commute, I will under-estimate their carbon emissions and overstate overall heterogeneity. On the other hand, if they walk or bike part of the distance of their commute, I will overestimate these household's carbon emissions and understate overall heterogeneity.

Allowing for heterogeneous vehicle fuel economy

In the baseline specification, I assign a national average fuel economy to all households. To explore the sensitivity of my results to this assumption, I construct three estimates of fuel economy using data from the NHTS, allowing for heterogeneity across geographic characteristics (CBSA, state, urbanity) only, individual and household characteristics (age, race, household size, household income, gender, number of vehicles, and commute mode of transit interacted with commute length) only, and both sets of characteristics. For each specification, I use a penalized Lasso regression to predict individual-level vehicle fuel economy based on the included set of characteristics, and then I use these estimates of mpg to estimate emissions from commuting.

Results are presented in the three "MPG" rows of Table G.9, and are not qualitatively different from baseline estimates.

Non-commuting transportation emissions:

I don't observe transportation other than commuting. In particular, I don't observe local travel for errands or leisure, nor do I observe airplane travel. Thus, I (weakly) underestimate carbon emissions magnitudes. If commuting is a rank-preserving share of total transportation emissions, my results will be qualitatively correct but off in magnitudes. However, if for example places with long commutes have lower other transportation emissions (because everybody spends leisure time in their back yard) whereas places with short commutes have higher other transportation emissions (because people go away for the weekend), then my estimates cannot be used to infer anything about heterogeneity in overall transportation emissions.

Estimating total vehicle miles traveled

In the baseline specification, miles commuted serve as a proxy for total vehicle miles. To explore the sensitivity of my results to this assumption, I also construct an estimate of total miles traveled by using a penalized Lasso regression to predict total miles from the set of both household and geographic variables described above in the NHTS data. Table G.9 shows that this does not meaningfully affect the results.

B The Leave-One-Out Connected Set

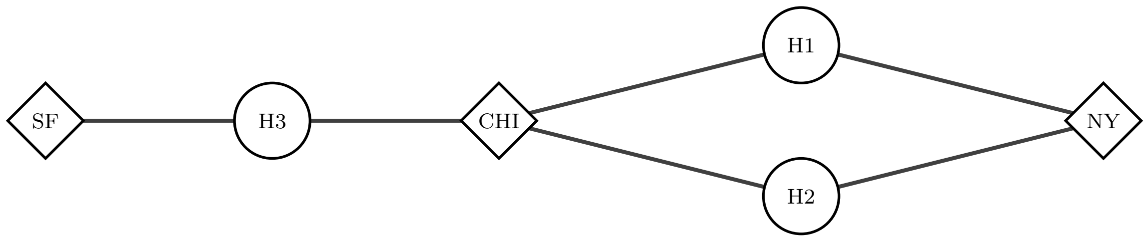
Consider the following data:

Individual & Household Geographic Locations

Year	Household	Place
1	1	NY
2	1	CHI
1	2	CHI
2	2	NY
1	3	SF
2	3	CHI

Household 1 moves from NY to Chicago, household 2 moves from Chicago to NY, and household 3 moves from San Francisco to Chicago. This data can be visualized as a network, where each place is a node, each household is a node, and edges connect households to each place they've lived in.

Household + Place Network



In this figure, San Francisco, Chicago, and New York are all connected by movers – this is a connected set. The leave-out connected set is the set of places that remains connected after dropping any household from the data. In this example, San Francisco is *not* in the leave-out connected set, because it is only connected to the rest of the network through H3.

C Empirical Bayes Adjustment

When discussing distributions of either observational means or place effects, I account for the fact that these parameters are noisily estimated by using linear Empirical Bayes, i.e. a shrinkage estimator. Many papers in the public and labor literatures have used this approach to predict for example teacher value add or neighborhood effects in other contexts (Chetty, Friedman, and Rockoff 2014a; 2014b; Angrist et al. 2017; Chetty and Hendren 2018; Finkelstein, Gentzkow, and Williams 2021; Abaluck et al. 2021). Although the linear approximation only corresponds to the true Empirical Bayes posterior when errors are normal and homoskedastic, Kline, Rose, and Walters (2021) show that even when errors are heteroskedastic, the linear shrinkage estimator doesn't do much worse than non-parametric Empirical Bayes. The shrinkage estimates are given by:

$$\hat{y}_j^{EB} = \lambda_j \hat{y}_j + (1 - \lambda_j) \frac{1}{J} \sum_j \hat{y}_j \tag{1}$$

where y represents the neighborhood-level parameter of interest, and the weights $\lambda_j = \frac{\hat{\sigma}_j^2}{s_j^2 + \hat{\sigma}_j^2}$ capture the signal-to-noise ratio of each estimate and down-weight noisy estimates to the grand mean.

D Model

Household i, living in place j, consumes quantity Q of energy in the form of four types of fuels: electricity (e), natural gas (n), other heating fuels (o), and motor gasoline (m). Each of these fuels has an emissions factor $\phi_{(jt)}$; these factors vary over time and place for electricity but are fixed along both of these dimensions for the other three fuel types. Household carbon emissions are therefore given by the following expression, with it subscripts temporarily supressed for easier legibility:

$$CO_2 = \phi^e_{jt} \cdot Q^e + \phi^n \cdot Q^n + \phi^o \cdot Q^o + \phi^m \cdot Q^m$$

Note that it is possible to re-express the above in terms of fuel shares, where for each fuel

$$s^f = \frac{Q^f}{\sum_f Q^f}$$

And therefore

$$CO_2 = \left(\sum_f s^f \cdot \phi^f_{(jt)} \right) \cdot Q$$

where, as before, Q represents total energy consumption across the four fuels.

Returning to **??**

$$\ln Q_{it} = a_j + \sum_{f \in \mathcal{F}} \rho^f_j \cdot \ln P^f_j + X_{it}\beta + \tau_t + \alpha_i + \varepsilon_{it}$$

it follows that

$$\ln CO_{2_{it}} = \ln \left(\sum_f s^f_{it} \cdot \phi^f_{(jt)} \right) + a_j + \sum_{f \in \mathcal{F}} \rho^f_j \cdot \ln P^f_j + X_{it}\beta + \tau_t + \alpha_i + \varepsilon_{it}$$

I add and subtract log of the average emissions factor, $\bar{\phi_j}$, which I used in the simplified exposition of the model in **??**, and rearrange terms to get the following expression:

$$\ln CO_{2_{it}} = \ln \bar{\phi_j} + a_j + \sum_{f \in \mathcal{F}} \rho^f_j \cdot \ln P^f_j + X_{it}\beta + \tau_t + \alpha_i + \varepsilon_{it} + \ln \left(\frac{\sum_f s^f_{it} \cdot \phi^f_{(jt)}}{\bar{\phi_j}} \right)$$

Observe that if not for the last term, this expression would be equivalent to **??**, but when household fuel shares vary, there is an interaction between household fuel shares relative to the average in the place where it lives, and place specific electricity emissions intensities. A household that disproportionately uses electricity wherever it lives will have a larger drop in emissions when moving from a place with relatively dirty electricity to a place with relatively clean electricity than the average household will. This variability gets absorbed by the error term in my regressions, and motivates the use of heteroskedastic errors.

E Computational Appendix

This section closely follows the description provided in KSS, as I replicate their method. I proceed in two steps, regressing $\log(CO_2)$ on observable characteristics and year fixed effects, and residualizing so that I am left with

$$\tilde{y}_{ij} = \alpha_i + \psi_j + \varepsilon_{it}$$

The share of overall variance attributable to place effects can then be captured by the variance component of place effects,

$$Var(\psi_j) \equiv \sigma_\psi^2 = \frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}(\psi_{j(i,t)} - \bar{\psi})^2$$

and the covariance component between place effects and person effects

$$Cov(\alpha_i, \psi_j) \equiv \sigma_{\alpha,\psi}^2 = \frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}(\psi_{j(i,t)} - \bar{\psi}) \cdot \alpha_i$$

KSS provides an estimate for the standard error $\psi_i^2 = Var(\varepsilon_i)$ based on a leave out estimate of σ_i^2:

$$\hat{\sigma}_i^2 = y_i(y_i - x_i'\hat{\beta}_{-i}) = y_i\frac{(y_i - x_i'\hat{\beta})}{1 - P_{ii}}$$

where $P_{ii} = x_i'(x_i x_i')^{-1}x_i$ is the observation leverage.

To reduce the computational burden of the KSS estimator, I use the Johnson-Lindenstrauss approximation (JLA) algorithm introduced by KSS to estimate the statistical leverages of each match, i.e. the amount by which estimates change when leaving out the match. KSS show that using JLA introduces an approximation error of roughly 10^{-4} relative to estimating statistical leverages directly. See KSS for a complete discussion of the leave-out estimator and JLA algorithm.

F The Evolution of Place Effects

Time-varying fixed effects:

I provide descriptive evidence on the changing nature of place effects from 2000-2019 in Appendix Figure G.8. Pooling all time-varying fixed effect estimates together and grouping pooled values into four quartiles, the vast majority of CBSAs either do not change rank or become lower emissions from the first period (2000-2004) to the last period (2015-2019), consistent with large declines in emissions from electricity production as a result of a dramatic decline in coal and increase in renewables (U.S. Energy Information Administration 2020). In contrast, defining quartiles within year, the distribution of whether CBSAs become relatively lower or higher emissions than their counterparts between those two periods is roughly symmetric, but with over half of CBSAs not changing relative rank.

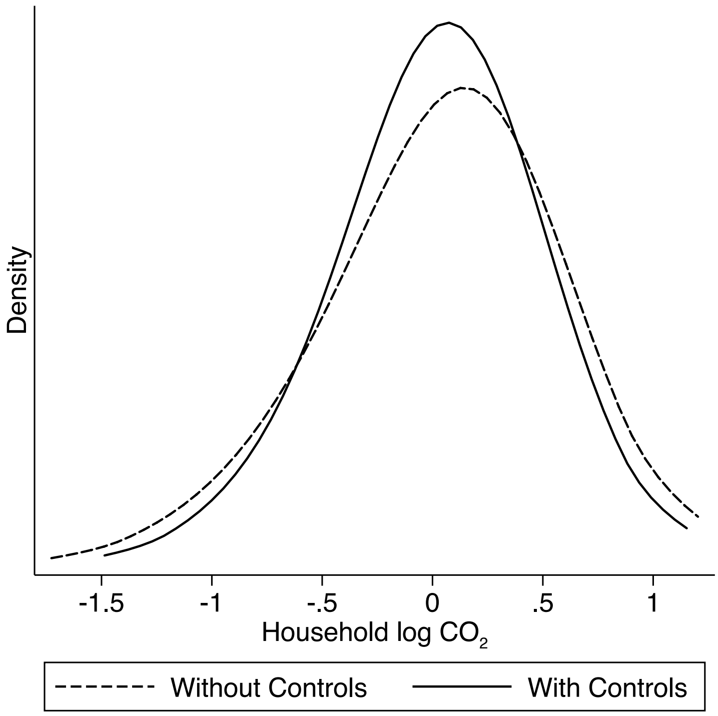
The impact of the COVID-19 pandemic:

There was likely a discontinuous change in CBSA effects following the COVID-19 pandemic and the shift to remote work, which was accompanied by a steep decline in commuting and a shift towards larger homes to accommodate home offices (Van Nieuwerburgh 2023; D'Lima, Lopez, and Pradhan 2022). Cicala (2023) finds that during the acute parts of the pandemic (Q2-Q4 of 2020), residential energy consumption increased by about eight percent, while the use of transportation fuel consumption declined by about 16 percent. The resulting increase in residential energy is likely to widen the gap in place effects between suburban and urban tracts, though the net impact on emissions should be modulated by the decrease in commercial energy. In contrast, the reduction in commuting is likely to decrease the gap between suburban and urban tracts. It is a limitation of my data that I only observe commuting miles, but in my sample time frame, using the NHTS to predict overall transportation from commuting does not substantively change the results. In the COVID-era this data limitation becomes prohibitive as commuting and overall transportation miles become completely disentangled. Finally, it is worth noting that while initially it seemed like there might be a permanent structural shift to remote work and a decline of cities (e.g. Gupta et al. 2022), as of 2024 it appears that many employers are requiring workers to return to the office (e.g. Resume Builder 2023), calling into question whether the pandemic will have had a long-term impact on cities. The net effect of all these countervailing forces, and the extent to which they result in a permanent, structural shift in place effects, is an empirical question which this paper does not have enough data to address at this time, but is an important avenue for future research.

G Additional Figures and Tables

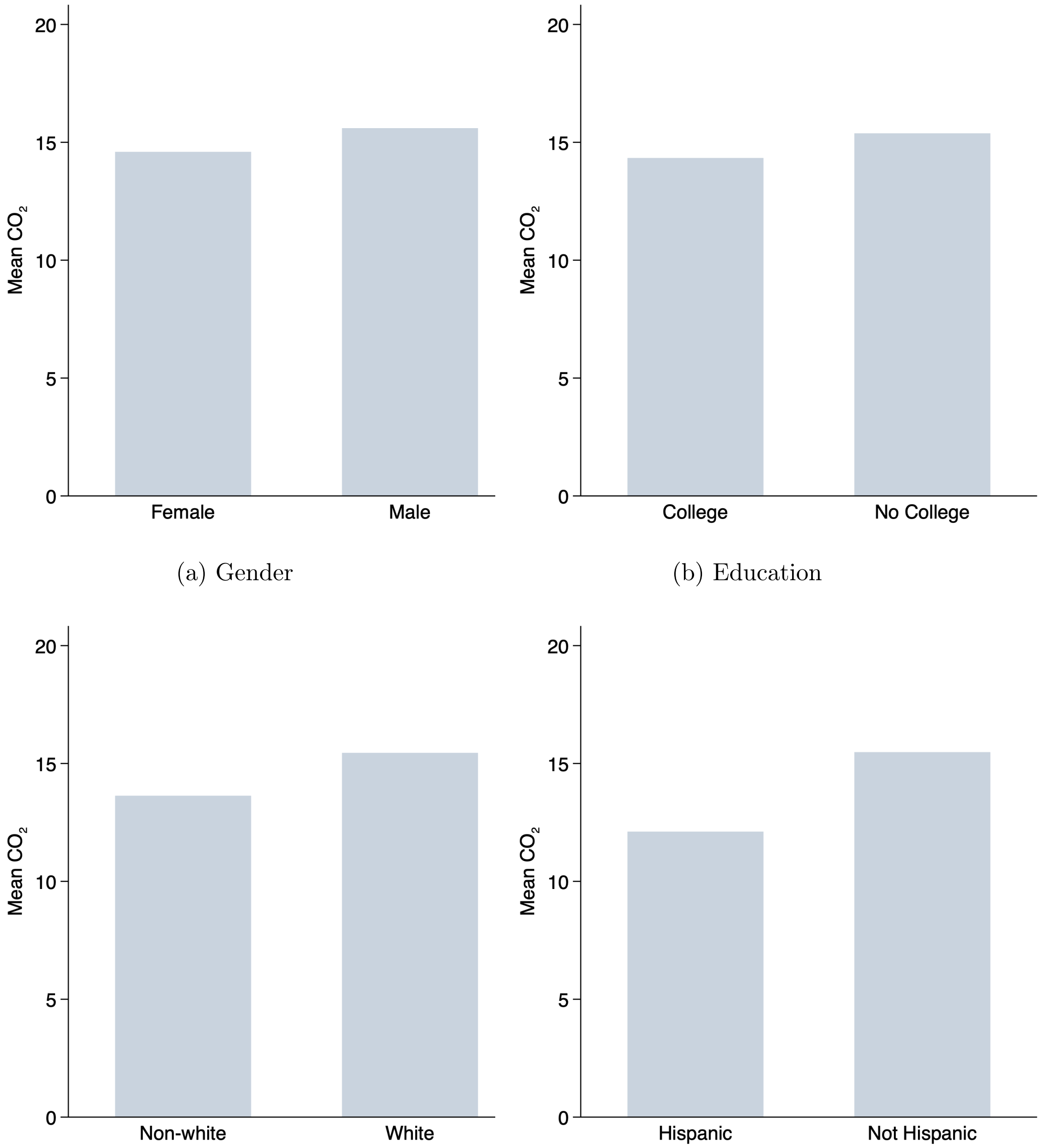
G.1 Additional Figures

Figure G.1: **Heterogeneity in Household Carbon Emissions**



Note: This figure shows Kernel Density estimates, using a Gaussian kernel function, of de-meaned household carbon emissions. Household carbon emissions are censored at the top and bottom 1% of observations in order to abide by Census Disclosure Avoidance rules. The dotted gray line labeled “Without Controls” corresponds to the distribution of log CO_2 conditional on year FEs only, and has a standard deviation of 0.59, while the solid line labeled "With Controls" conditions on observable household characteristics, and has a standard deviation of 0.52. Observable characteristics include age, gender, race, ethnicity, education, home owner status, household income, household size, and number of children.

Figure G.2: CO_2 Profiles by Demographic Characteristics (1/4)



(a) Gender

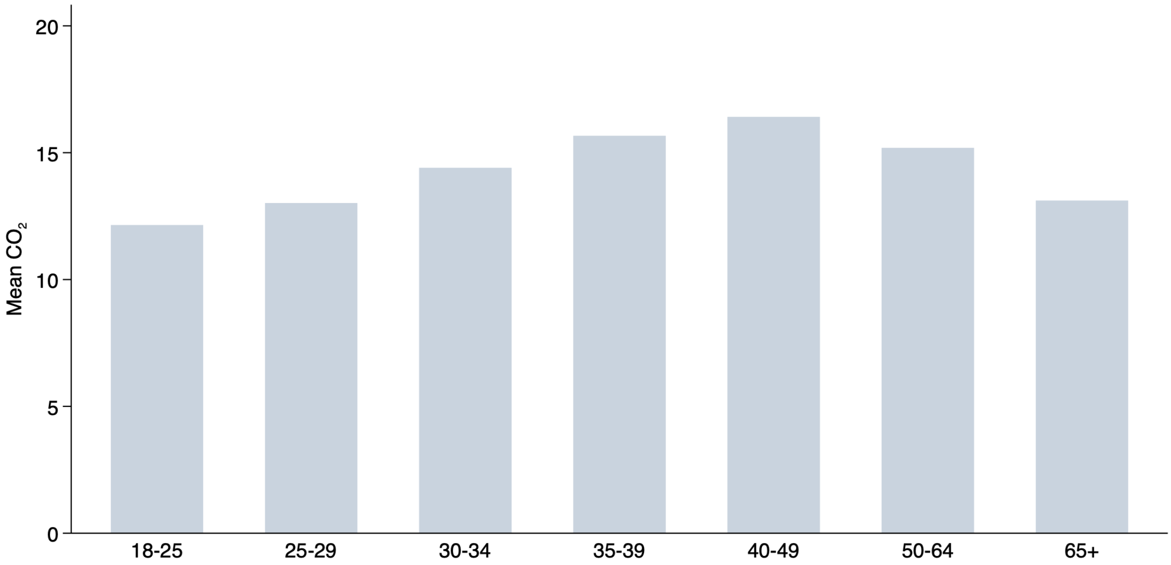
(b) Education

(c) Race

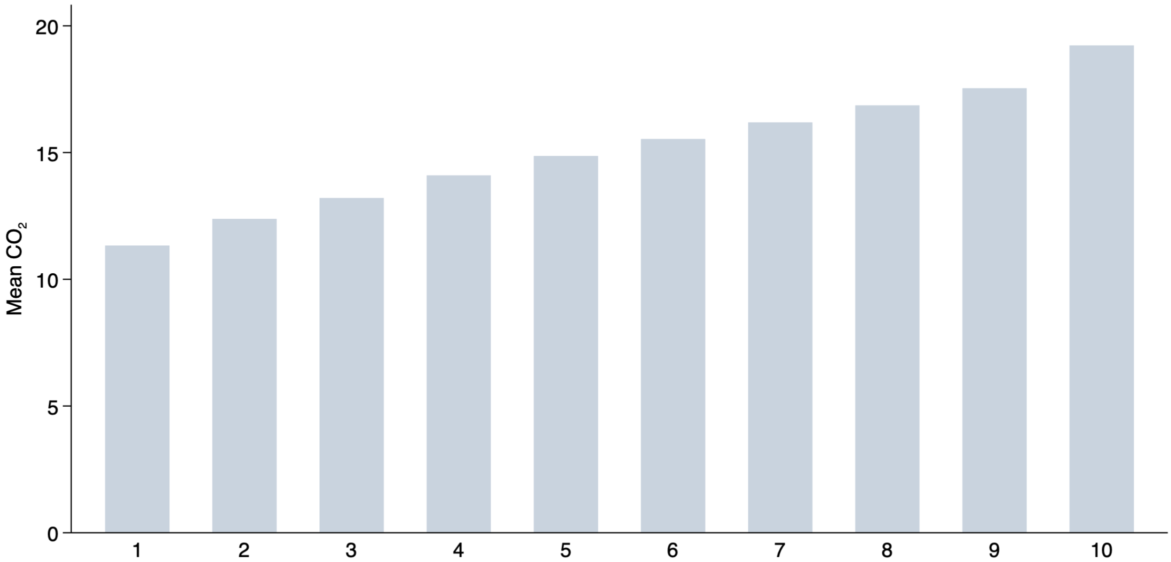
(d) Ethnicity

Note: This figure shows variation in household carbon emissions by household member demographics. Panel (a) shows that households with more women (age 18+) have slightly lower emissions (consistent with women having fewer and shorter commutes). Panel (b) shows that college educated households have slightly lower emissions. Panel (c) and (d) show large differences by race and ethnicity – white households and non-Hispanic households have higher emissions on average than non-white and Hispanic households. All estimates reflect the full sample, pooled 2000-2019, weighted by Census sample weights.

Figure G.3: CO_2 Profiles by Demographic Characteristics (2/4)



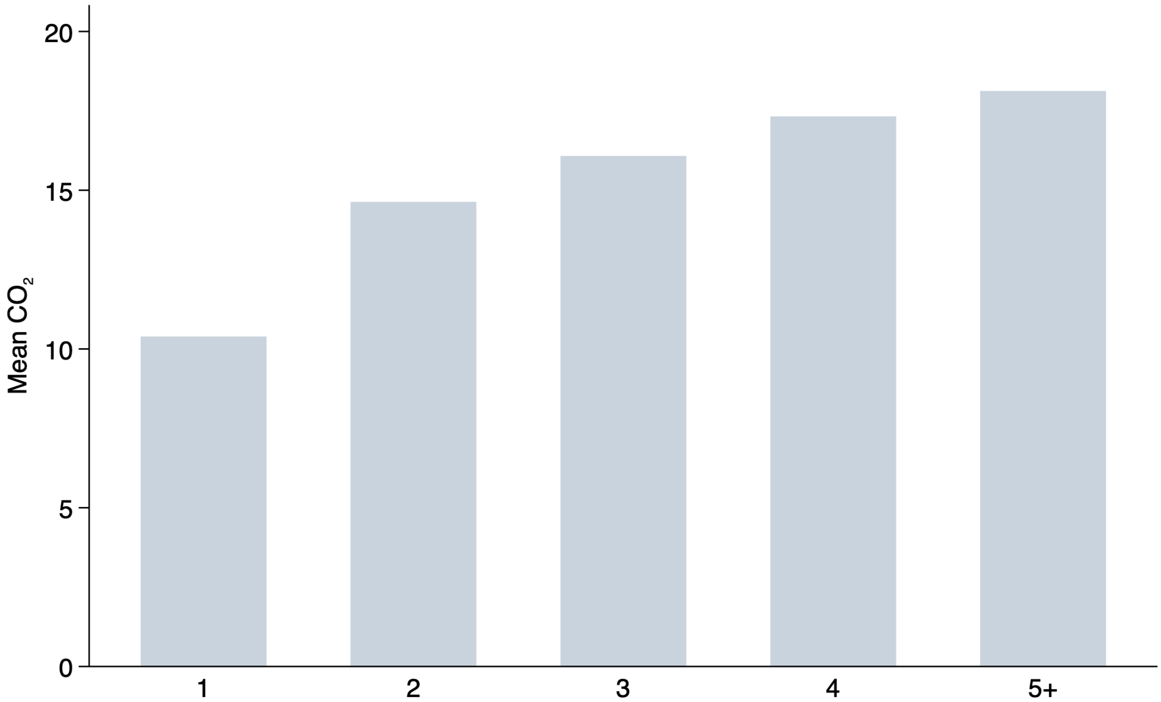
(a) Age



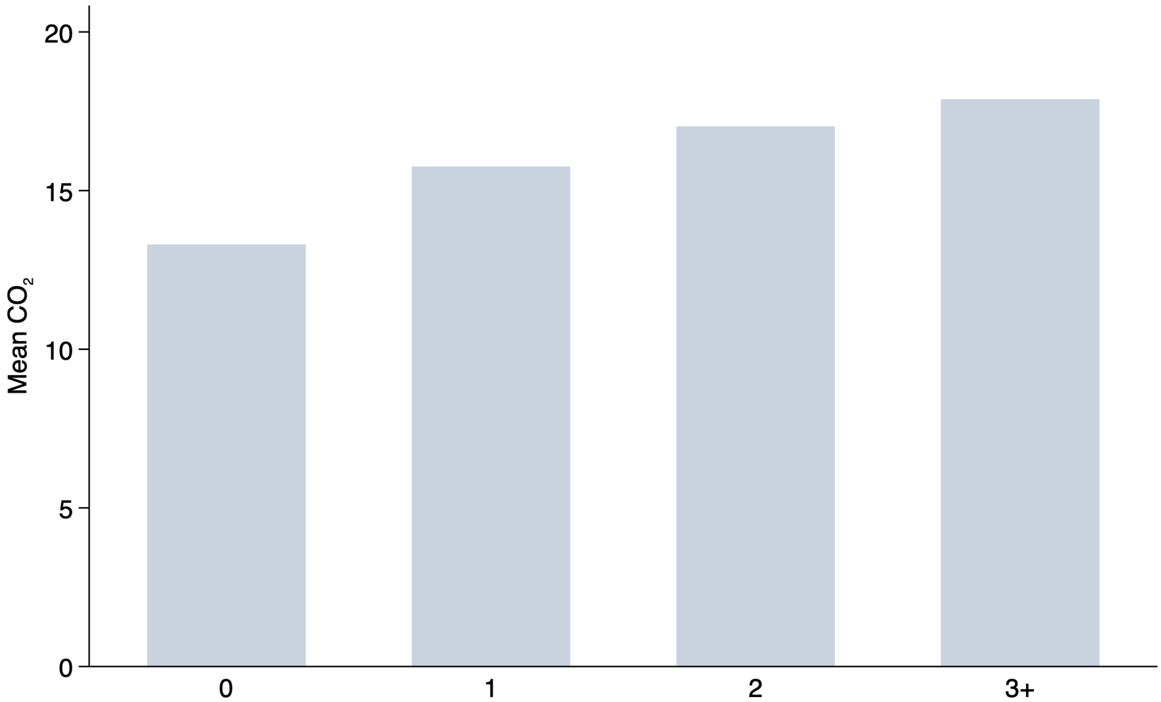
(b) Income Decile

Note: This figure shows variation in household carbon emissions by household member age and household income deciles. Panel (a) shows a non-linear relationship between the adult age of household members and mean carbon emissions which increases through people's 40s and then decreases again (likely reflecting a combination of higher incomes and children still being in the home). Panel (b) shows an increasing relationship between household income decile and carbon emissions. All estimates reflect the full sample, pooled 200-2019, weighted by Census sample weights. Household income is CPI-adjusted.

Figure G.4: CO_2 Profiles by Demographic Characteristics (3/4)



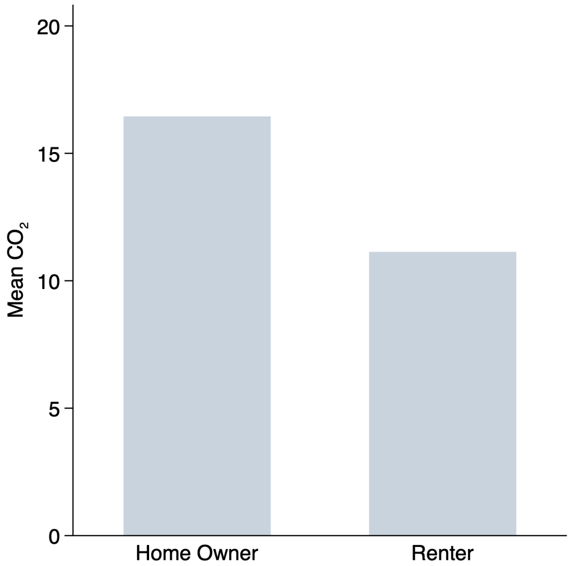
(a) Household Size



(b) Number of Kids

Note: This figure shows variation in household carbon emissions by household size (a) and number of children (b). Carbon emissions increase with household size and with the number of children, but less than proportionally, and the increase is fairly small going from 4 to 5+ people, or 2 to 3+ kids. All estimates reflect the full sample, pooled 200-2019, weighted by Census sample weights.

Figure G.5: CO_2 Profiles by Demographic Characteristics (4/4)

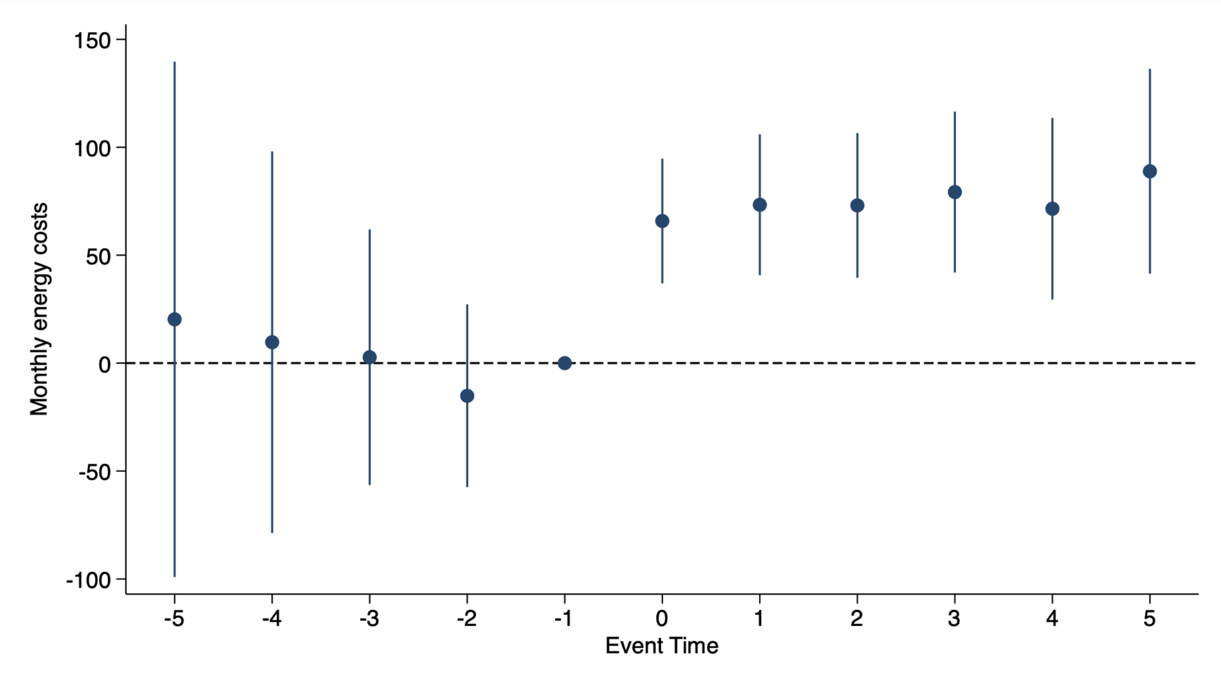


(a) Home Ownership

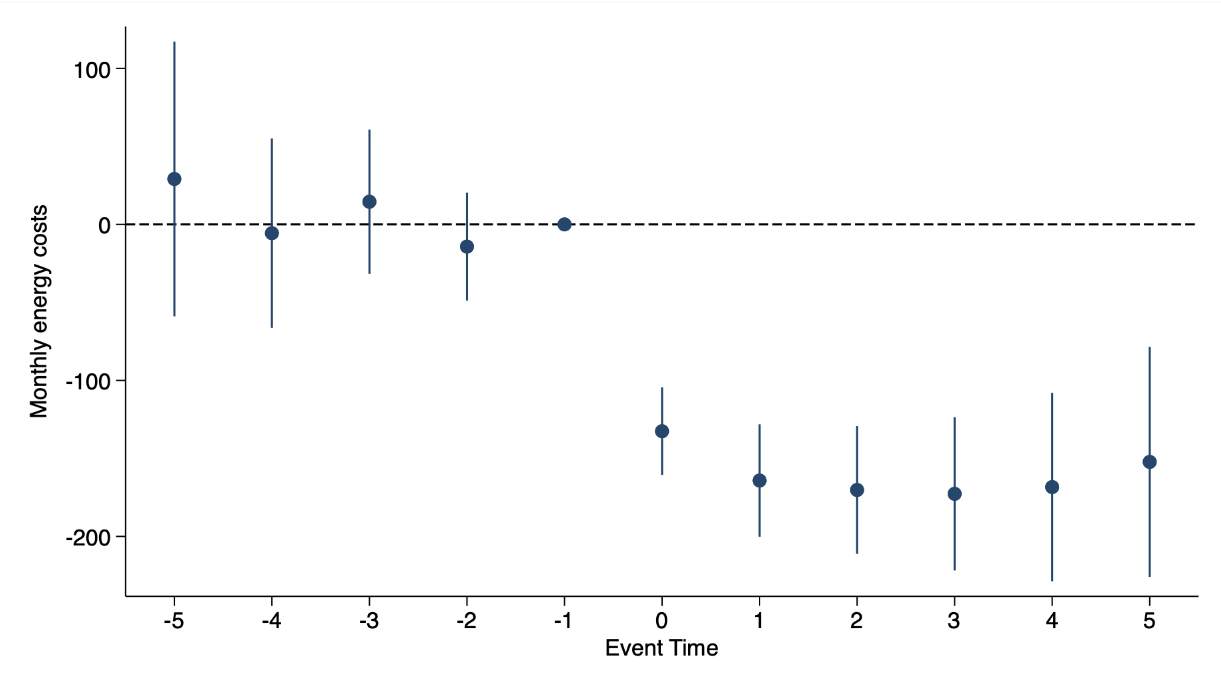
Note: This figure shows variation in household carbon emissions by homeowner status, highlighting that renters have lower emissions on average than homeowners. All estimates reflect the full sample, pooled 200-2019, weighted by Census sample weights.

Figure G.6: Energy Expenditures in Mover Households in the PSID

(a) Households with higher expenses after move

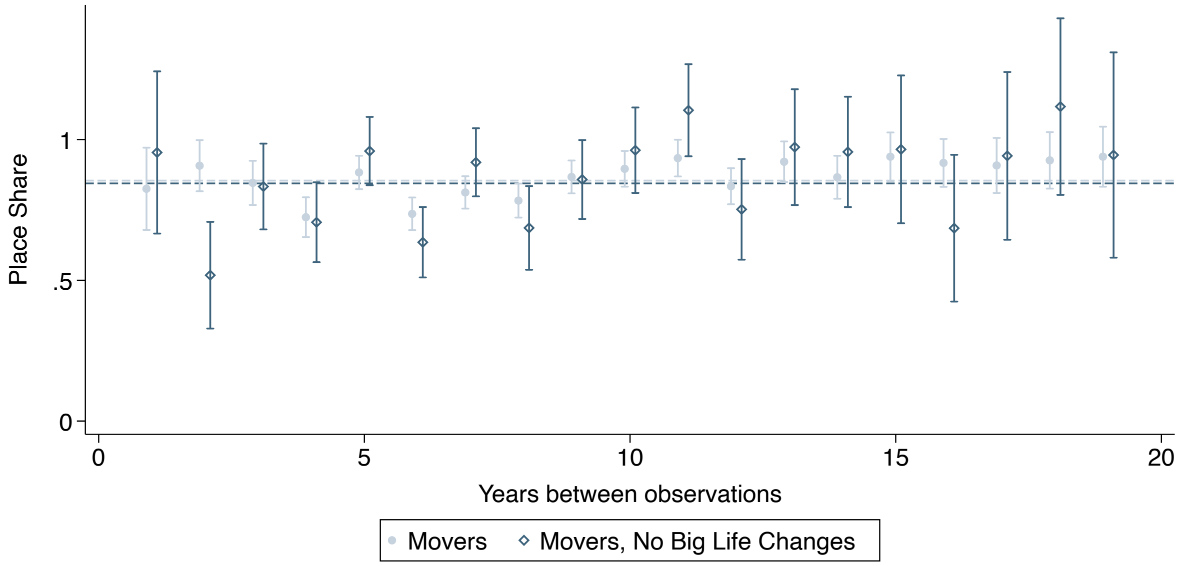


(b) Households with lower expenses after move



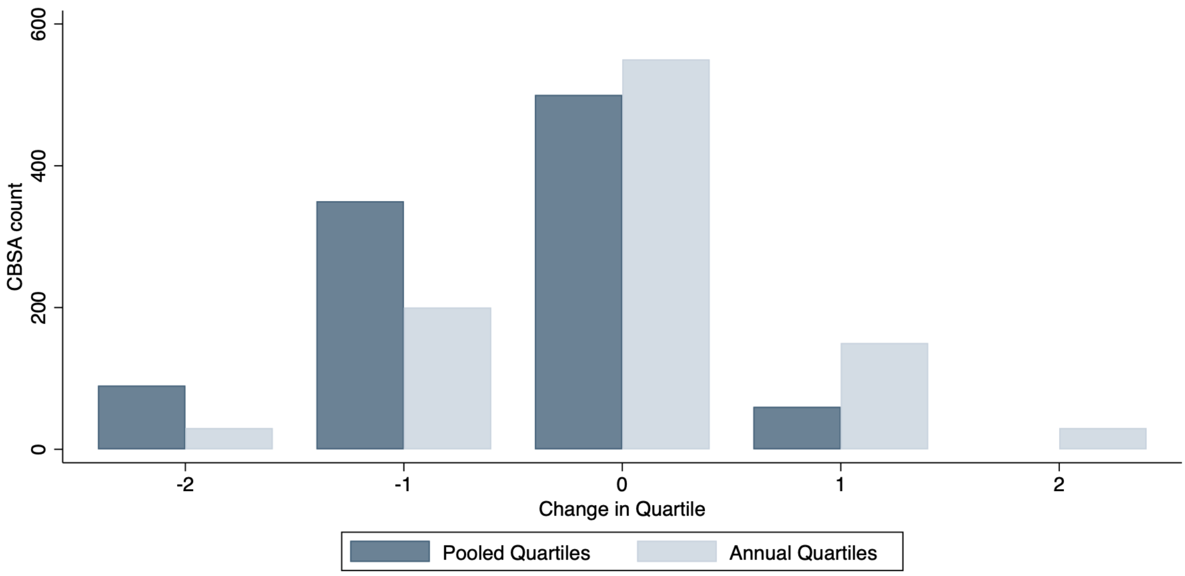
Note: I examine whether there are pre-trends in energy consumption for movers using data from the PSID, given data limitations in my baseline data. In particular, I test whether there are significant changes to monthly energy expenses (residential energy bills + gasoline expenses) in the years prior to a move, after controlling for household size, income, head of household age, and year fixed effects. Because I do not observe where households move to, I examine households who spend more on average after moving and households who spend less on average after moving separately. Neither group exhibits pre-trends.

Figure G.7: **Event study by duration – CBSA**



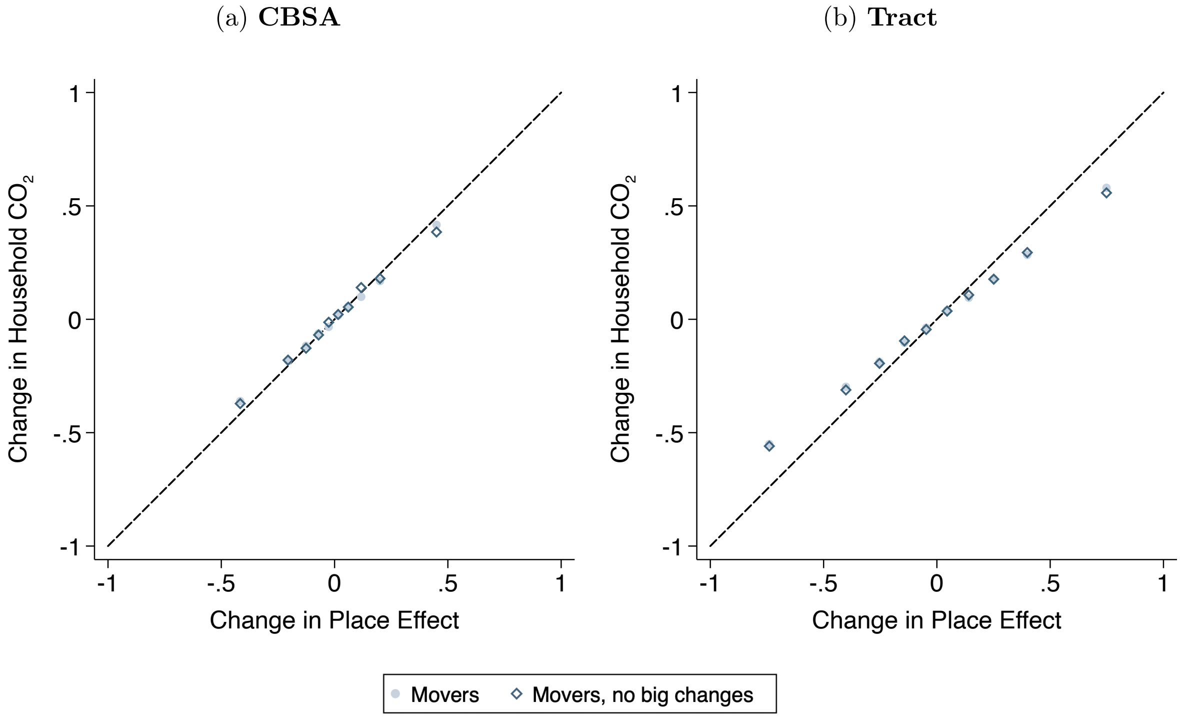
Note: This figure shows event study estimates of the share of spatial variation in mean carbon emissions that can be explained by place effects, by duration between mover observations. In other words, each coefficient is the estimate for place effects generated from the sub-sample of households that I observe X years apart. Coefficients plotted in light gray circles are estimated from the model using the entire sample of movers. Coefficients plotted in the dark blue diamonds are estimated from the model using the sub-sample of movers with no change in the number of children, a less than 0.5 log point change in household income, and no change in home-ownership status between observations. All estimates are weighted using Census sample weights.

Figure G.8: **Changes in Time-Varying CBSA Effect Ranks**



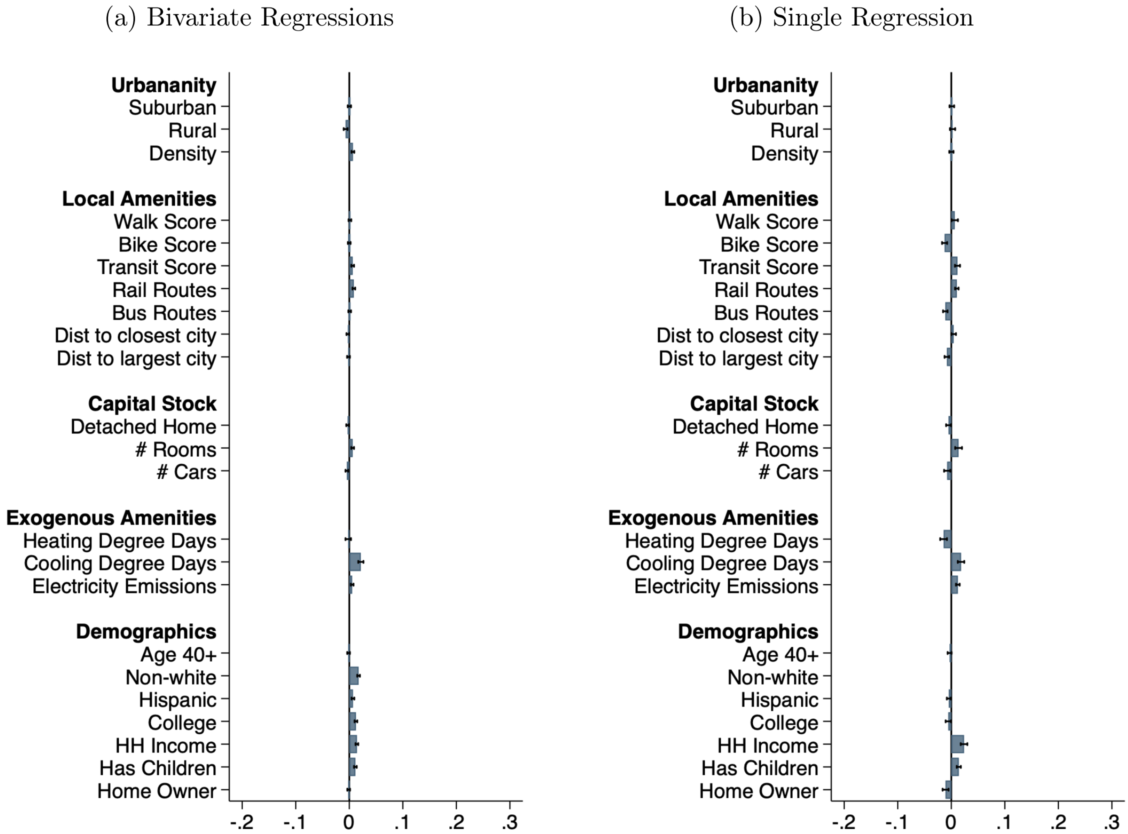
Note: This figure shows the distribution of rank changes in time varying CBSA effects from the 2000-2004 period to the 2015-2019 period. The dark blue bars show changes in pooled quartiles, while the light blue bars show changes in within-year quartiles.

Figure G.9: **Place Effects vs. Household Carbon Emissions**



Note: This figure shows event study estimates of the share of spatial variation in mean carbon emissions that can be explained by place effects, by size of origin-destination differences in the KSS estimates of place effects. The two sets of points compare the full sample of movers (solid light grey circle) to the sub-sample of movers with no change in the number of children, a less than 0.5 log point change in household income, and no change in home-ownership status between observations (empty dark blue diamond). The dotted black line shows the 45°line. All estimates are weighted using Census sample weights.

Figure G.10: **Correlates of Unobserved Household Heterogeneity**



Note: This figure presents estimates from OLS regressions of estimated tract effects on a set of observable place-based and household characteristics. Panel (a) shows results from separate bivariate regressions, while panel (b) shows results from a single regression on all covariates. All amenity variables are tract level means, normalized to have mean zero and standard deviation one, except the rural and suburban indicators, which are retained as indicators. Regressions are weighted using ACS sample weights.

G.2 Additional Tables

Table G.1: **Summary Statistics for Sample Dropped Due to Missing Energy Info**

	Full				Panel	Mover	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	Elec in Rent	Gas in Rent	Gas in Elec.	All	CBSA	Tract
A: Demographics							
College	0.31	0.21	0.28	0.33	0.33	0.41	0.36
Age	42	40	39	43	44	40	41
White	0.72	0.67	0.68	0.74	0.83	0.83	0.81
Female	0.48	0.46	0.48	0.48	0.48	0.45	0.48
Household Income	85,010	51,800	65,310	98,860	100,800	102,700	100,100
Household Kids	0.9	0.7	0.6	1.0	0.9	0.9	0.9
Household Size	2.6	2.2	2.1	2.8	2.7	2.7	2.6
Homeowner	0.47	0.10	0.16	0.67	0.65	0.53	0.55
B: Outcomes							
Tons CO_2 - Commute	2.5	1.7	1.8	3.0	2.6	2.7	2.5
C: Intermediate Outcomes							
Detached Home	0.44	0.15	0.08	0.65	0.60	0.54	0.52
Use Electricity Only	0.04	0.24	0	0	0.09	0.14	0.12
Commute by Car	0.83	0.70	0.70	0.89	0.88	0.88	0.88
Commute Minutes	25.4	23.9	25.4	25.7	25.0	25.0	25.5
D: Place Characteristics							
Urban	0.34	0.44	0.47	0.28	0.26	0.25	0.28
Suburban	0.18	0.15	0.19	0.18	0.15	0.12	0.15
Rural	0.48	0.41	0.34	0.54	0.59	0.64	0.57
Walk Score	46.1	53.8	59.3	40.2	38.3	36.2	39.7
Bike Score	47.5	52.3	55.6	43.8	43.2	43.5	44.5
Transit Score	18.8	23.7	26.6	15.2	14.4	14.0	15.9
N Bus Routes	4.7	6.9	7.9	3.3	3.5	3.5	3.8
N Rail Routes	0.93	1.24	1.84	0.54	0.63	0.55	0.65
Cooling Degree Days	947	1,110	924	919	932	1,062	983
Heating Degree Days	5,028	4,754	5,236	4,993	5,272	5,021	5,151
N People	1,810,000	389,000	722,000	980,000	165,000	24,500	68,000
N Households	1,410,000	322,000	593,000	721,000	272,000	44,500	121,000
CBSAs	1,000	1,000	1,000	950	950	950	950
Tracts	68,500	53,000	56,500	55,000	49,000	26,000	43,000

Note: This table shows summary statistics for households dropped from the analysis as a result of having their electricity bills included in rent, their natural gas bills included in rent, or their natural gas bills included in their electricity bills. Column (1) shows statistics for the entire set of households who would've been in the full sample but got dropped for any one of those three reasons. Columns (2)-(4) show summary statistics broken out by group. Column (5) shows summary statistics for the sub-sample of column (1) who would've been in the panel sample if not for these unobserved bills, and columns (6) and (7) show households who would have been in the mover sample. All statistics are weighted by ACS household weights.

Table G.2: **Panel Statistics for Sample Dropped Due to Missing Energy Info**

		Movers	
	(1) Panel	(2) CBSA	(3) Tract
A: Sample Characteristics			
First Observed in 2000	0.08	0.13	0.12
Years Between Observations	8.6	10.4	9.9
B: Demographic Characteristics			
Age First Observed	40.6	34.8	35.9
Share with Large Change in Income	0.43	0.62	0.56
Share with Change in N Kids	0.44	0.51	0.51
Change in N Kids	0.03	0.30	0.23
Share Rent to Own	0.22	0.39	0.38
C: Mover Place Changes			
Δ Walk Score		-7.8	-7.7
Δ Bike Score		-5.1	-4.9
Δ Transit Score		-2.7	-3.6
Δ N Bus Routes		-0.96	-1.22
Δ N Rail Routes		-0.06	-0.15
Δ Tract Share Detached Home		0.07	0.08
% Moves Urban-to-Urban		0.19	0.28
% Moves Urban-to-Suburban		0.22	0.21
% Moves Suburban-to-Suburban		0.34	0.32
Δ Cooling Degree Days		146	122
Δ Heating Degree Days		-265	-159
N People	165,000	24,500	68,000
N Households	142,000	22,000	60,000
CBSAs	950	950	950
Tracts	49,000	26,000	43,000

Note: This table shows panel statistics for households dropped from the main analysis as a result of having their electricity bills included in rent, their natural gas bills included in rent, or their natural gas bills included in their electricity bills. The Column (1) shows statistics for households who would have been in the panel if not for unobserved billing information, while Columns (2)-(3) show statistics for households who would have been in the mover sample. All statistics are weighted by ACS household weights.

Table G.3: **Mean CO_2 – Movers vs. Stayers**

	CBSA Panel				Tract Panel			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mover	-0.07***	-0.05***			-0.11***	-0.08***		
	(0.001)	(0.001)			(0.001)	(0.001)		
Mover x Orig.			-0.12***	-0.05***			-0.08***	-0.04***
			(0.002)	(0.002)			(0.001)	(0.001)
Mover x Dest.			-0.04***	-0.04***			-0.03***	-0.03***
			(0.001)	(0.001)			(0.001)	(0.001)
Cons.	2.64***	2.58***	2.64***	2.59***	2.67***	2.61***	2.65***	2.61***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
Controls	No	Yes	No	Yes	No	Yes	No	Yes

Note: This table compares household carbon emissions for movers and stayers. Columns (1)-(2) and (5)-(6) compare movers overall to stayers overall, with and without controls. Movers have lower carbon emissions than stayers, with a slightly less pronounced difference after controlling for differences in income and other demographic characteristics. Columns (3)-(4) and (7)-(8) present within-comparisons of stayers and movers within a given place. The “Mover x Orig." coefficient compares movers with stayers at their origin, while the “Mover x Dest." coefficient compares movers with stayers at their destination. Movers have lower emissions than stayers at both their origin and their destination. The origin difference looks more pronounced in the specifications without controls, but is effectively the same as the destination difference after controlling for observable household characteristics. All estimates are weighted by ACS household sample weights.

Table G.4: **Probability of Moving**

	(1) Moved CBSA	(2) Moved Tract
Decrease in Kids	0.02***	0.05***
	(0.001)	(0.001)
Increase in Kids	0.06***	0.18***
	(0.001)	(0.001)
Large Decrease in Income	0.06***	0.13***
	(0.001)	(0.001)
Large Increase in Income	0.09***	0.16***
	(0.001)	(0.001)
Rent $\rightarrow$ Own	0.16***	0.48***
	(0.001)	(0.002)
Constant	0.06***	0.19***
	(0.000)	(0.001)
R^2 (adj.)	0.05	0.17

Note: This table shows that households with a change in the number of children at home, a larger than 0.5 log point change in income, or who go from renting to owning are much more likely to move than stay. This is most pronounced for households who go from renting to owning their home, and is also more pronounced for positive changes in children or income than negative changes. All estimates are weighted by ACS household sample weights.

Table G.5: **Mover Origin and Destination Types**

(a) CBSA Movers

	To Rural	To Suburban	To Urban	Total Share
From Rural	0.03	0.09	0.01	0.13
From Suburban	0.07	0.44	0.09	0.60
From Urban	0.01	0.17	0.08	0.26
Total Share	0.11	0.50	0.18	1.00

(b) Tract Movers

	To Rural	To Suburban	To Urban	Total Share
From Rural	0.03	0.06	0.01	0.10
From Suburban	0.05	0.46	0.09	0.60
From Urban	0.01	0.17	0.14	0.32
Total Share	0.09	0.69	0.24	1.00

Note: This table shows shares of origin-destination tract types for CBSA movers (panel (a)) and tract movers (panel (b)). The most common type of move, for both CBSA and tract movers, is from a suburban tract to another suburban tract. Moves between urban and rural tracts are exceedingly uncommon. All estimates are weighted by ACS household sample weights.

Table G.6: **Event Study – with Climate and Electricity Emissions Controls**

	CBSA		Tract	
	(1)	(2)	(3)	(4)
A: Panel Sample				
Place share of mean difs.	0.86***	0.70***	0.60***	0.54***
	(0.007)	(0.012)	(0.003)	(0.004)
N	1,764,000	1,764,000	1,710,000	1,710,000
R^2 (adj.)	0.75	0.75	0.76	0.77
B: Mover Sample				
Place share of mean difs.	0.85***	0.68***	0.57***	0.51***
	(0.009)	(0.014)	(0.004)	(0.004)
N	191,000	191,000	508,000	508,000
R^2 (adj.)	0.70	0.71	0.73	0.73
Household controls	X	X	X	X
Climate & electricity controls		X		X

Note: This table reports event study estimates of the place share of spatial heterogeneity in household carbon emissions. The place share estimate ($\hat{\theta}$) represents the proportion of differences in average carbon emissions ($\bar{y}$) between a mover's origin and destination attributable to place effects. Panel A reports estimates from the panel sample, while panel B restricts the sample to movers only, allowing for systematic differences between movers and stayers. Columns (1) and (3) replicate the baseline analysis presented in **??**. Columns (2) and (4) add controls for mean heating degree days, mean cooling degree days, and mean electricity emissions factors. All estimates use Census sample weights.

Table G.7: **Place-Based Heterogeneity in CO_2 – Climate vs Electricity Emissions**

	CBSA				Tract			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel Sample								
Variance of log(CO_2)	0.31	0.31	0.31	0.31	0.31	0.31	0.31	0.31
Share attributable to places	0.163	0.146	0.080	0.074	0.228	0.217	0.151	0.152
Share attributable to hhs	0.496	0.496	0.494	0.494	0.363	0.362	0.362	0.361
Corr. of place and hh effects	0.013	0.036	-0.003	0.027	0.016	0.070	0.024	0.081
SD of place effects	0.23	0.21	0.16	0.15	0.26	0.26	0.22	0.22
Mover Sample								
Variance of log(CO_2)	0.35	0.35	0.35	0.35	0.33	0.33	0.33	0.33
Share attributable to places	0.140	0.125	0.046	0.039	0.218	0.220	0.145	0.155
Share attributable to hhs	0.136	0.129	0.160	0.156	0.099	0.098	0.102	0.101
Corr. of place and hh effects	0.073	0.102	0.048	0.084	0.084	0.160	0.084	0.161
SD of place effects	0.22	0.21	0.13	0.12	0.27	0.27	0.22	0.23
Climate		X		X		X		X
Electricity CO_2			X	X			X	X

Note: This table reports KSS estimates of variance components, deliniating between the contribution of local climate conditions vs the contribution of local electricity emissions factors. All specifications include demographic and household controls as well as time fixed effects. To ease comparison, Columns (1) and (5) replicate baseline estimates shown in columns (1) and (5) of **??**, while columns (4) and (8) of this table replicate estimates accounting for the contribution of both climate and electricity emissions factors simultaneously (i.e. columns (2) and (6) of **??**). Columns (2) and (6) of this table show estimates accounting for just the role of climate in the variance components, while Columns (3) and (7) show estimates accounting for just the role of electricity carbon emissions. All estimates are weighted by ACS household sampling weights.

Table G.8: **Place-Based Heterogeneity in CO2 – No Bias Correction**

	CBSA				Tract		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel Sample							
Variance of log(CO_2)	0.31	0.31	0.31	0.31	0.31	0.31	0.31
Share attributable to places	0.175	0.086	0.090	0.188	0.523	0.449	0.453
Share attributable to hhs	0.558	0.554	0.554	0.557	0.748	0.747	0.746
Corr. of place and hh effects	-0.026	-0.028	-0.027	-0.026	-0.417	-0.429	-0.427
SD of place effects	0.23	0.16	0.17	0.24	0.40	0.37	0.37
Mover Sample							
Variance of log(CO_2)	0.35	0.35	0.35		0.33	0.33	0.33
Share attributable to places	0.153	0.051	0.053		0.461	0.399	0.403
Share attributable to hhs	0.505	0.502	0.502		0.582	0.581	0.581
Corr. of place and hh effects	0.008	-0.008	-0.005		-0.291	-0.298	-0.294
SD of place effects	0.23	0.13	0.14		0.39	0.36	0.37
Climate + Electricity CO_2		X	X			X	X
Price Index			X				X
Time-Varying FEs				X			

Note: This table reports results from the biased AKM estimation of variance components. All specifications include demographic and household controls as well as time fixed effects. Columns (1) and (5) report the baseline variance decompositions at the CBSA and tract levels. Columns (2) and (5) add controls for local mean heating degree days, cooling degree days, and electricity emissions factors (all in logs). Columns (3) and (6) additional control for a price index, constructed from lagged fuel shares interacted with national retail prices. Finally, column (4) computes time-varying CBSA place effects using 5-year windows (2000-2004, 2005-2009, 2010-2014, and 2015-2019), using stayer observations across time windows to identify time variation in place effects, while movers, as before, identify cross-sectional variation. All estimates are weighted by ACS household sampling weights.

Table G.9: **Place-Based Heterogeneity in CO_2 – Alternate Outcome Definitions**

	CBSA				Tract			
	V(y)	S(ψ_j)	S(α_i)	corr.	V(y)	S(ψ_j)	S(α_i)	corr.
Panel Sample								
Baseline	0.31	0.163	0.496	0.013	0.31	0.228	0.363	0.016
Electricity Emissions Estimates								
Marginal Emissions	0.34	0.236	0.470	-0.016	0.337	0.295	0.343	-0.011
Variable Prices	0.33	0.155	0.498	0.018	0.321	0.218	0.363	0.026
Decreasing Block Prices	0.35	0.150	0.503	0.016	0.341	0.216	0.373	0.011
Increasing Block Prices	0.31	0.186	0.480	0.013	0.303	0.246	0.345	0.033
Selected Block Prices	0.32	0.159	0.500	0.014	0.311	0.220	0.366	0.024
Transportation Emissions Estimates								
Commute from hrs	0.29	0.160	0.487	0.015	0.287	0.206	0.367	0.024
Commute from hrs, fixed num.	0.29	0.168	0.487	0.009	0.286	0.213	0.366	0.020
MPG from NHTS (dem. only)	0.32	0.169	0.495	0.008	0.313	0.235	0.365	0.006
MPG from NHTS (geo. only)	0.32	0.173	0.493	0.011	0.313	0.240	0.363	0.007
MPG from NHTS	0.32	0.174	0.490	0.011	0.312	0.238	0.360	0.010
Total Transportation from NHTS	0.20	0.177	0.468	0.037	0.200	0.218	0.376	0.015
Mover Sample								
Baseline	0.35	0.140	0.136	0.073	0.333	0.218	0.099	0.084
Electricity Emissions Estimates								
Marginal Emissions	0.39	0.219	0.136	0.004	0.378	0.281	0.094	0.025
Variable Prices	0.36	0.133	0.135	0.077	0.349	0.209	0.100	0.088
Decreasing Block Prices	0.39	0.131	0.136	0.069	0.372	0.207	0.105	0.062
Increasing Block Prices	0.34	0.161	0.137	0.067	0.329	0.240	0.097	0.091
Selected Block Prices	0.35	0.138	0.134	0.073	0.336	0.211	0.097	0.086
Transportation Emissions Estimates								
Commute from hrs	0.32	0.142	0.132	0.070	0.310	0.202	0.101	0.089
Commute from hrs, fixed num.	0.32	0.149	0.132	0.063	0.309	0.210	0.099	0.075
MPG from NHTS (dem. only)	0.36	0.145	0.138	0.070	0.341	0.221	0.102	0.077
MPG from NHTS (geo. only)	0.36	0.150	0.138	0.076	0.341	0.227	0.100	0.083
MPG from NHTS	0.35	0.150	0.138	0.075	0.341	0.225	0.097	0.089
Total Transportation from NHTS	0.21	0.169	0.171	0.0772	0.207	0.214	0.118	0.0862

Note: This table reports KSS estimates of variance components, using a variety of different outcome definitions to test robustness of the baseline estimates. Estimates are reported for both the full panel sample (top half of table) and the mover only sample (bottom half of table). Each outcome definition is a row in the table, with baseline estimates replicated in the first row of each sample to ease comparability. Outcome variants are grouped into two categories: one which impacts residential carbon emission estimates, and one which estimates transportation emissions estimates. Overall variance of the outcome, the share attributable to place effects, the share attributable to person effects, and the correlation between place and household effects are reported at the CBSA level in columns (1)-(4), respectively, and at the tract level in columns (5)-(9). All estimates are weighted by ACS household sampling weights.

Table G.10: **Place Correlates w/ Observable Characteristics**

	College	Age > 40	Non-white	HH Income	Has Kids	Homeowner
Density	-0.002*	0.004***	0.006***	0.033***	0.017***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Suburban	0.014***	0.005***	-0.025***	0.015***	-0.010***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Rural	0.001	0.009***	-0.025***	-0.028***	-0.019***	-0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Walk Score	0.002*	0.006***	-0.022***	0.025***	0.007***	-0.021***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
Bike Score	0.025***	-0.011***	-0.004***	0.027***	-0.006***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Transit Score	0.006***	0.004***	0.027***	0.030***	-0.007***	0.006***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
CDD	-0.015***	0.000	-0.063***	-0.044***	0.003	0.025***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
HDD	-0.030***	-0.003***	-0.103***	-0.070***	-0.012***	0.033***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
Elec. CO_2	-0.018***	-0.020***	0.008***	-0.062***	-0.010***	-0.004***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
N Rail Routes	0.007***	0.002***	-0.012***	0.036***	0.002	0.010***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
N Bus Routes	0.016***	-0.003***	-0.012***	0.016***	-0.013***	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Detached Home	-0.043***	0.009***	-0.000	-0.085***	0.013***	0.047***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
N Rooms	0.121***	0.055***	-0.004***	0.309***	0.032***	0.071***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
N Vehicles	-0.036***	0.017***	-0.055***	0.076***	0.043***	0.041***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Dist. Closest City	-0.013***	-0.005***	-0.011***	-0.041***	-0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Dist. Largest City	0.005***	0.012***	0.010***	0.064***	0.007***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.25***	0.63***	0.14***	11.29***	0.53***	0.78***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
Adj. R^2	0.451	0.465	0.326	0.643	0.155	0.767

Note: This table reports correlation coefficients between tract-level mean observable household characteristics and a detailed vector of observable place characteristics. All estimates are weighted by ACS household sampling weights.

Table G.11: **10 most populous CBSAs (2020)**

Rank	CBSA
1	New York-Newark, NY-NJ-CT-PA
2	Los Angeles-Long Beach, CA
3	Chicago-Naperville, IL-IN-WI
4	Dallas-Fort Worth, TX-OK
5	Houston-The Woodlands, TX
6	Washington-Baltimore-Arlington, DC-MD-VA-WV-PA
7	Philadelphia-Reading-Camden, PA-NJ-DE-MD
8	Miami-Port St. Lucie-Fort Lauderdale, FL
9	Atlanta-Athens Clarke County-Sandy Springs, GA-AL
10	Boston-Worcester-Providence, MA-RI-NH-CT

This table presents the ten most populous CBSAs as of 2020, which are used in the analysis evaluating how overall emissions would change under different distributions of place effects. Source: U.S. Census Bureau (2024)

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